Modelling user interactions in the Internet of Things

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ABSTRACT

User experience with 'smart' objects determines the device's adoption. One important consideration, therefore, is whether it is possible to model the interactions prior to development, so that design decisions can be made which could enhance user experience. In this paper, we focus on the use of Task Analysis for Error Identification (TAFEI) as a tool for Internet of Things (IoT) systems modelling. Based on the concept of identifying and characterising the purpose of the social-like interactions, we analyse how goals are achieved when using an instrumented object. TAFEI provides a perspective in which Human-Internet of Things Interaction (HII) is analysed from the context of system's goals and sub goals. As such, this approach not only provides system's failure scenarios, but more appropriately for IoT enabled objects, it also enables the identification of new scenarios for the system to provide knowledge to the user, and allow it to predict a user's intent and pre-emptively take action on the user's behalf. This methodology allows Internet of Things development to not only consider sensor data, but also system usability, promoting meaningful HII, and improving user engagement with IoT systems.

KEYWORDS

HCI, usability, Internet of Things.

Introduction

The last two decades have seen significant advances in the fields of integrated circuit development, power management and communications, allowing for Internet of Things (IoT) devices to shift from the passive data collection objects that were originally conceived (Smith & Konsynski, 2003), to *things* that actively engage with their environment, other *things*, and human users (Kortuem et al., 2010). As such, from the simple RFID enabled objects used in the IoT's inception, *things* have evolved to complex objects imbued with varying degrees of agency, intelligence and autonomy (Fortino, 2016). Moreover, marketing literature promises that between the IoT and the mobile Apps ecosystem, objects would be connected to each other, allowing for flawless service composition, effectively creating a blanket of smartness that would make common activities easier for the users (Bojanova et al., 2014). Market leaders, such as Intel, have promised ecosystems that would improve efficiency, safety, providing a richer experience to users, so that devices:

"*Will become smart enough to function on their own, making real-time decisions, learning from their environment, and using that learning to improve performance*" (Intel, 2017).

A consequence of this techno-centric vision is that users become nodes in the IoT network; acting on the edge of the control loops, or as passive recipients of the actions of 'smart' things. As such, success in device adoption often relies, amongst other circumstances, on user experience, which determines whether the product would survive its hype, by providing a useful and meaningful service to its user (Kuniavsky, 2010).

Drawing upon strands of research in Task Analysis and Human-IoT Interaction (HII), this paper focuses on the use of Task Analysis for Error Identification (TAFEI) as a tool for IoT systems modelling, with the goal of predicting user intent and promoting meaningful HII interactions.

Background

In the IoT, objects are 'enhanced' through a digital representation of their physical attributes (Schroeder et al., 2016), whilst creating connections with other objects and its users. Kelly (2017) defines these enhanced objects as 'cognified', possessing characteristics that allow them to be able to share aspects on where they are situated, status of their surroundings, and how or when they were used. As such, these devices generate data that can be broadly categorized by three types: location, environmental and social. The network permutations permitted through this model, allows for an IoT in which nodes tend to engage in collaborative relationships to achieve a common goal. When introducing human users, Human-IoT Interaction falls within the realm of social data, where associations between objects and humans are heavily influenced by the user's requirement to obtain a purposeful result (Nunes et al., 2015). In this environment, it is often the case that devices and human users must negotiate their role within this association. However, much like any other relationship, it is expected that some sort of benefit will be obtained from it. Particularly, in the case of the human user, the anticipation would be to obtain insight on the 'smart' device's goal, such as added convenience and comfort, richer user experiences or possibly even knowledge (such as calories burnt in a wearable fitness tracker, or energy consumed in a smart electric meter). In a way, the interactions imply that there is a common interest in reaching such goals, analogous to a mutually beneficial social relationship. Aztori et al. (2014) have analysed this inter-device and device-user collaboration from the point of view of social-like organisations. Cila et al. (2017) define these bidirectional interactions as a "conversation amongst social actors". It has been suggested that these conversations are required in order to establish a collaborative sense-making process (Preece et al., 2015), and that these 'IoT actors' participate towards common aims and achieving rules through an emphasis and understanding of the system's purpose, as opposed to hard-code rules (Cervantes-Solis et al., 2015). However, a dissociation on the objects' affordances and their virtual representation can lead to misunderstanding the smart object's purpose and intent, primarily due to a lack of information and communication on what exactly it is that the system is trying to achieve (Yang & Newman, 2013). Moreover, it has been argued that in order for physical objects to have any value or meaning to users, they must hold an instance of social data attached to them (Speed, 2011). This implies that objects must be used and appropriated in order to become meaningful for a person. In fact, it has been argued that the most important requirement for interaction is not the ability to use an object, but the engagement they support with the user (Golightly, 1996).

As mentioned, the experience that users have when interacting with 'cognified objects becomes a crucial aspect for their adoption, and analysis of how to provide better engagement with them is an emerging field of Human-Computer Interaction (HCI) (Koreshoff et al., 2013). Thus, IoT system modelling has been approached from different perspectives, such as semantic and ontology modelling (Wang et al., 2013) or the services they can provide. Nonetheless from an usability point of view, it has been argued that specifically for IoT objects, affordances "cannot immediately communicate to people their actual values and meanings" (Matassa & Simeoni, 2015), creating a rift on how users engage with the system, and understand its purpose. This paper aims to provide a framework in which IoT systems can be modelled to provide meaning, based on the concept of identifying and characterising the purpose of the social-like interactions, and by analysing how tasks and goals are achieved in an instrumented object.

System usability has been approached in ergonomics and HCI by a different range of methodologies, focusing on analysis of user actions. Hierarchical Task Analysis (HTA) (Stanton,

2006) has been used as a means of providing system requirements through a representation of the system's sub goals, and used in different applications such as user interface design, workload design and assessment and error prediction. An extension of HTA was defined by Task Analysis for Error Identification (TAFEI) (Baber & Stanton, 1994), originally conceived as a tool to analyse a system's usability through system actions, and the possible errors derived from them. With the system's goals at its core, TAFEI provides a very interesting approach to model meaningful user interactions, which, as previously discussed are focused on a system's ability to provide a social-like collaboration amongst its participants to achieve a common goal. In the context of the IoT, TAFEI provides a perspective in which HII interactions are analysed from the perspective of a system's valid (or invalid, which in this tool's case are errors) goals and sub goals.

This study builds upon the concept of instrumented objects in everyday situations. In them, users interact with the objects, performing activities to achieve a goal. By doing so, they engage in a social like conversation, in which the collaborative environment is explained through the notion of a conversation with *topics* and *themes* (Cervantes-Solis & Baber, 2016). In this context, the overarching themes of the conversations become the system's main goals, as described by TAFEI analysis.

Methodology

Although the IoT is envisioned as a collection of objects, this study focuses on the model for a single, fully instrumented object within a network of instrumented objects. By concentrating on only one object, it is expected to obtain a complete worked example of how TAFEI fits as a tool for IoT modelling. As such, a coffee machine was instrumented by placing sensors wherever user interaction is expected, as shown in Figure 1. Additionally, as will be described later, for TAFEI this also acts as the 'system image' for user interaction. To provide independence on sensor technologies and behaviours, all sensor outputs where standardised to their most basic 'on' and 'off' states. Hence, data were logged in a binary format reflecting the state of each of the system's points of interaction, and consequently, the device's state. Finally, IBM's Node-Red IoT [1]was used as the middleware for system integration and data collection.

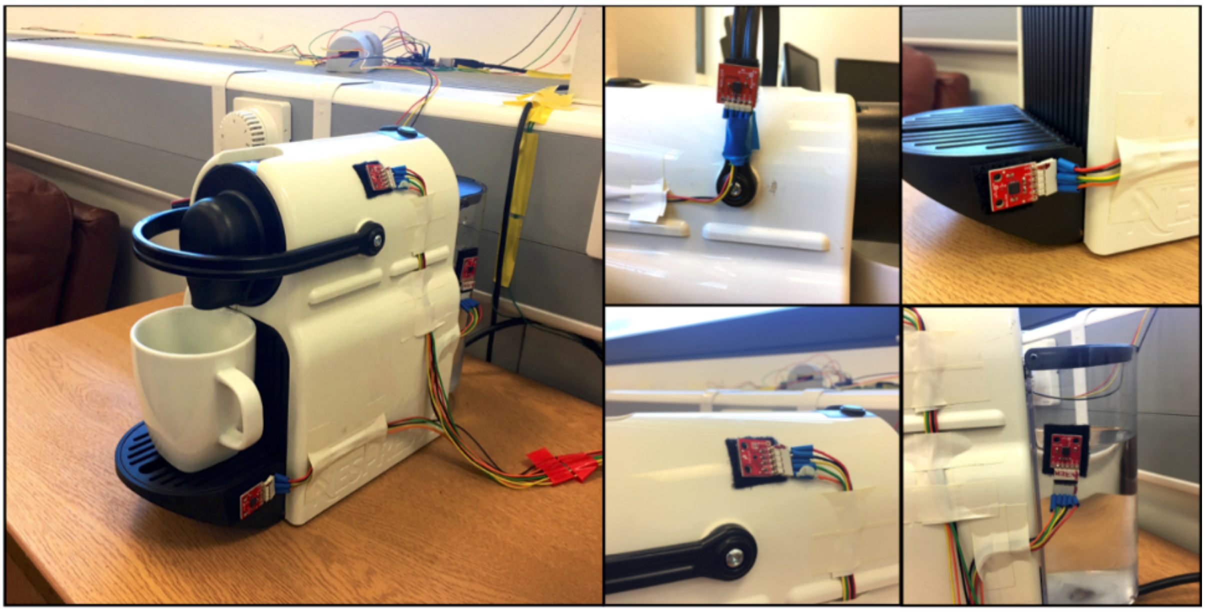

Figure 1: (Clockwise) Instrumented coffee machine and brew button sensor, handle sensor, empty capsule canister sensor, water tank sensor, and temperature sensor.

[1] http://nodered.org/

The work reported in this paper explores the deviations that the instrumented object can take, and the impact they have on the identification of the system's theme by a user. Thus, by observing these deviations, themes not previously considered in the system's design could be identified, allowing for a system's possible extension of functionality. Figure 2 shows a State-Space Diagram (SSD) of coffee machine's primary mode of operation. This SSD represents an analysis of the interactions found in the system, as a network of transitional states, in which each state provides a representation of the system being used as originally intended (its main goal). TAFEI requires the specification of the main system's goals, aiming to minimise the number of possible states. As previously described, this paper focuses on the association of users and objects in a social-like environment, hence, TAFEI's main goal are interpreted as the theme of the association. In the case of the instrumented coffee machine, the theme is defined thorough the most basic action it provides: 'Make a cup of coffee' (Theme 1). Through this analysis, TAFEI also allowed for a characterisation of possible errors in the system's usability.

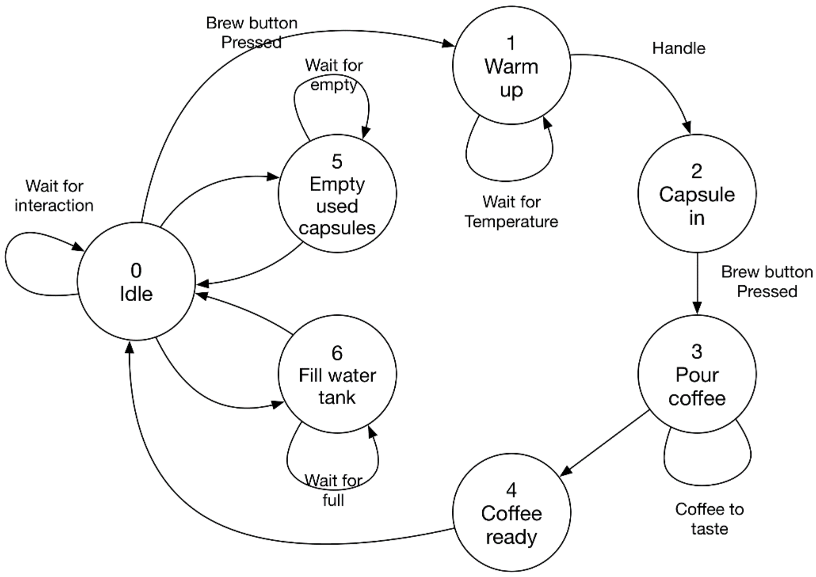

Figure 2: State diagram for coffee making theme

As part of its methodology, TAFEI suggests an analysis of the interactions from a user perspective. As such, Figure 3 shows the Hierarchical Task Analysis (HTA) for a user accomplishing the 'coffee-making' theme. Figure 4 shows the TAFEI diagram for the desired goal, including the definition of plans towards its completion described by the HTA in figure 3. Focusing on user interactions with the object, it can be observed that some of the transitions do not require the intervention of the user, such as waiting for the machine to warm up.

Summarising the state and HTA diagram analysis, Table 1 shows the system's TAFEI transition matrix, in which legal transitions for the 'Make a cup of coffee' theme are marked as 'L'. Notably, TAFEI is generally used to identify errors in product usability design. Notwithstanding, in the context of devices that can potentially be imbued with a notion of intelligence, the description of interactions that are not part of the main theme becomes a tool to establish different goals that are either actions that performed by the system or that through interactions with other parts of the system would enable secondary goals or themes. Notably, the former might not require user intervention as it might be implied by the system's or device's embedded intelligence, and could enable additional knowledge to the user. By observing the illegal and impossible transitions (marked as 'I' and '-', respectively) in the main goal's state diagram (figure 2), states 5 and 6, relate to filling up the coffee machine's water tank and emptying the used capsule container, hence a secondary theme emerges in the form of 'Coffee machine servicing' (Theme 2).

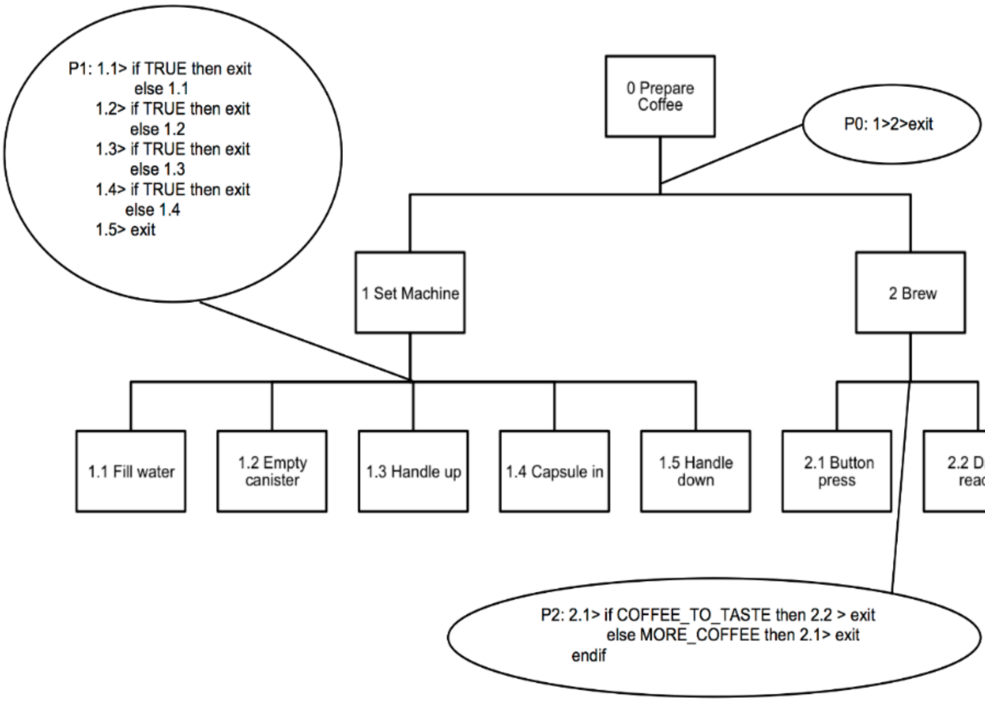

Figure 3: HTA for ‘coffee making’ theme

Table 1: Transition matrix for ‘Make a cup of coffee’ theme. Highlighted in green is the path leading for the successful completion of the goal. In yellow, although invalid for the analysed theme, an emergent secondary theme is enabled, showing the required path for the secondary Coffee machine servicing’ goal.

		To State						
		0	1	2	3	4	5	6
From State	0	I	L	-	-	-	-	I
	1	-	-	L	I	-	-	I
	2	I	-	I	L	I	-	I
	3	I	-	I	I	L	-	I
	4	-	-	-	-	I	L	-
	5	I	-	-	I	L	I	L
	6	I	I	I	I	-	-	I

The detailed breakdown of all the required plans and actions in the system, allows for its interpretation as a network where state transitions occur towards the achievement of a particular goal. As such, one of the aims of this study was to produce a framework in which an IoT system could be modelled and implemented in in a real-life environment. Using the Node-RED programming language as a development environment proved to be a suitable alternative for implementation, as it follows a flow programming paradigm, in which nodes become part of a network, following a set of rules provided by the governing logic. By using the information described in by the TAFEI diagram and Transition matrix, it is possible to provide a model of the system in terms of programmable function nodes within Node-Red as shown in Figure 5, akin to the state transitions shown in table 1. In addition to being a tool to conveniently translate SSDs into code, subsequent logic can be implemented with ease, allowing for experimentation with decision-making nodes.

Plans defined in the HTA diagram, where user action is expected, are used to label transitions in the TAFEI diagram and could be used to provide system cues to improve user interaction. Similarly, states that provide more than one transition (such as the one in found in table 1 from state 5 to state 4 or 6, given the possibility that the user might want more coffee from the same capsule) could be identified as ‘problematic’ and trigger user cues in the communication exchange.

For example, as presented in figure 5, by the system could detect when some of the described conditions are met, and then communicate with the user through a tweet using the Twitter API (or any other available mechanism enabled by the IoT middleware).

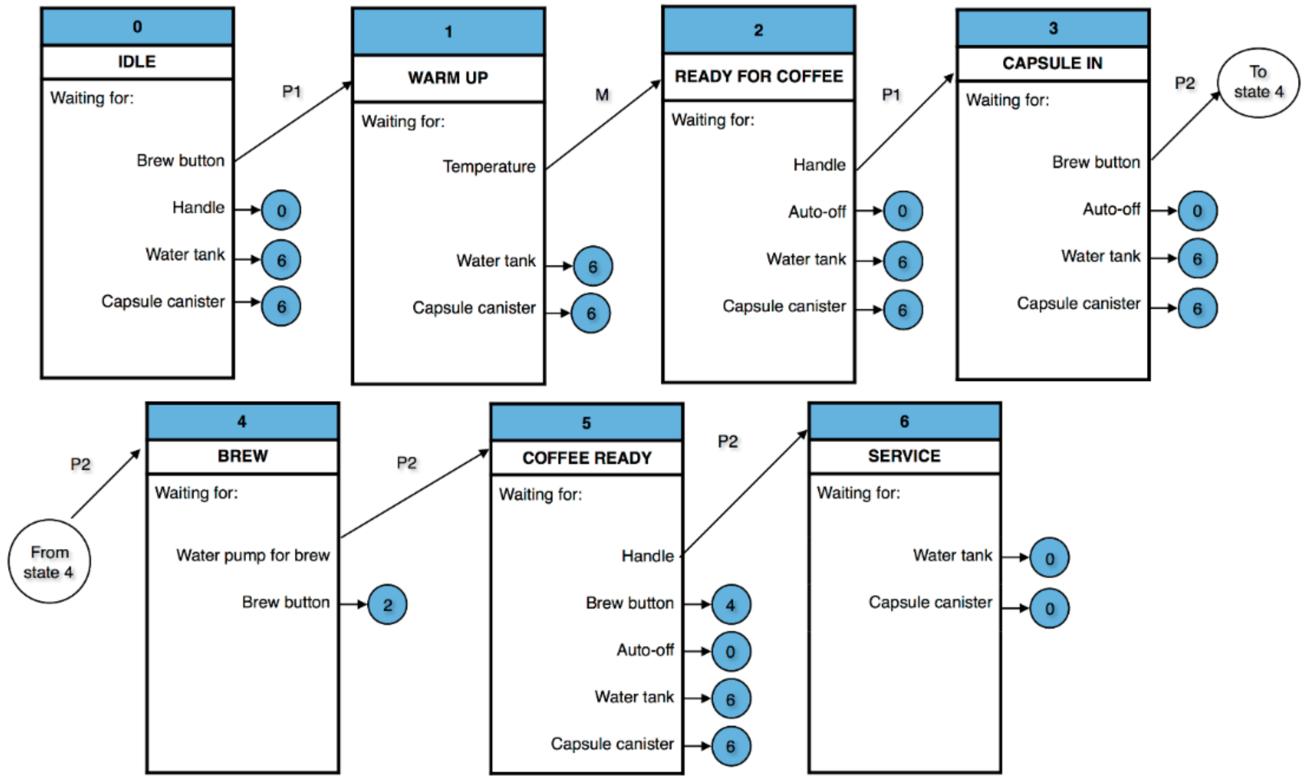

Figure 4: TAFEI diagram for ‘coffee making’ theme, showing plans users take to accomplish the desired goal. P1 and P2 correspond to user enabled interactions, whilst M is an action expected from the machine

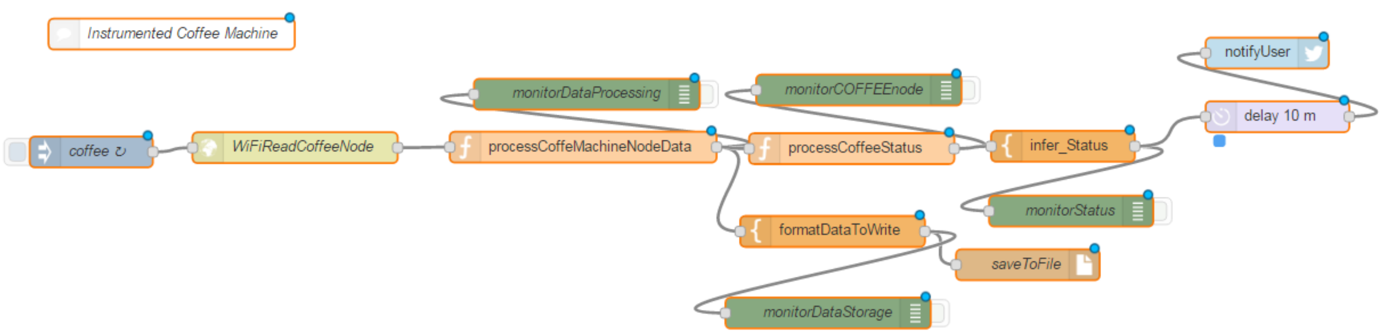

Figure 5: Node-RED program flow for the analysed coffee machine

Discussion

As the IoT permeates into more human-in-the-loop applications, and objects rely not only on their physical attributes, but also on their digital representations, the relationships they hold with users are affected, sometimes in unexpected ways. When objects are 'cognified', an additional layer of information is available to users. As such, affordances as traditionally interpreted, are not the only method for an object to convey information on how to interact with it and what they are for (their goal, or when the object gets socially linked to other objects or users, their theme).

By repurposing TAFEI's original aim of modelling systems focusing on errors as users attempt to carry out their main goal, we show how for instrumented objects it is possible to observe how the system's functionality could be extended, but more importantly, to provide a framework in which intelligence can be embedded into the system. When devices that traditionally were not considered 'smart', such as a coffee machine, become IoT enabled, they have extended capabilities and present opportunities for proactive and intelligent behaviour. These scenarios would allow a system to predict a user's intent and to provide them with additional information.

In this initial study a simple instrumented object was used as a way demonstrate TAFEI's suitability as a modelling tool for an IoT system's goals. In the described coffee machine scenario, the '[coffee making' *theme* (it's main goal) is clear, with precisely defined states, plans and transitions. With additional sensors, such as the one found in the coffee machine's water tank and discarded coffee capsules container, it is possible to describe the states required to identify their capacity level (empty or full water tank; capsules overfilling the canister), defining additional *topics* and interactions available to the system, enabling a new 'servicing' *theme*, facilitating the knowledge of whether the water tank needs to be filled or the capsule container replaced.

In conclusion, by applying TAFEI it was possible to identify at least one additional use-case for the evaluated system. As part of further development, this methodology will be applied to a larger scale system comprised of multiple instrumented devices. We expect that the application of TAFEI analysis would allow the consideration of human factors in the design of IoT systems and smart objects, alongside decision based. By allowing users to become more aware of the system's themes, meaningful interactions and user engagement would be promoted, enhancing IoT adoption.

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